## **UNCLASSIFIED**

# Defense Technical Information Center Compilation Part Notice

## ADP010890

TITLE: Automatic Detection of Military Targets Utilising Neural Networks and Scale Space Analysis

DISTRIBUTION: Approved for public release, distribution unlimited

This paper is part of the following report:

TITLE: New Information Processing Techniques for Military Systems [les Nouvelles techniques de traitement de l'information pour les systemes militaires]

To order the complete compilation report, use: ADA391919

The component part is provided here to allow users access to individually authored sections of proceedings, annals, symposia, ect. However, the component should be considered within the context of the overall compilation report and not as a stand-alone technical report.

The following component part numbers comprise the compilation report:

ADP010865 thru ADP010894

UNCLASSIFIED

## Automatic Detection of Military Targets utilising Neural Networks and Scale Space Analysis

#### A. Khashman

Chairman, Department of Computer Engineering Near East University Lefkosa, KKTC, Mersin 10 Turkey

E-mail: amk@neu.edu.tr or amk@ebim.net

**Summary:** This paper reports on a new approach to detecting military targets. The novel idea is based on combining neural network arbitration and scale space analysis to automatically select one optimum scale for the entire image at which object edge detection can be applied. Thus, introducing new measures to solve many of the problems existing in the discipline of image processing, such as: 1) poor edge detection in medium-contrast images 2) speed of recognition and 3) high computational cost. This new approach to edge detection is formalized in the Automatic Edge Detection Scheme (AEDS).

#### I. Introduction

Recent operations in conflict areas around the world have made the need for accurate image processing and fast target detection for military systems more obvious. In Kosovo, for example, a civilian tractor convoy was mistakenly targeted as enemy military target. Therefore, there is a need for more advanced intelligent target recognition systems.

A novel approach to target detection is presented within this paper. It is based on combining the three fields of scale space analysis, edge detection and neural networks. The result is an automatic edge detection scheme (AEDS) that delivers very quick edge detection of objects within medium-contrast images, through the automatic selection of a single optimum scale for applying the scale space edge detection to an entire image. The computational cost is kept to a minimum through using a fast edge detection operator combined with the power of a successfully trained neural network that recognizes only one correct scale (referred to as the ideal sigma  $\sigma_{Ideal}$  in this paper) for the entire image, out of the many available scales possible in scale space. Noise sensitivity and scale dependency can be problematic in image recognition. In this novel approach, both phenomena have been utilised to create a criterion upon which the ideal edge scale for optimum edge clarity will be chosen.

The proposed AEDS is expected to overcome the common problems that are experienced when implementing image recognition. These are: speed, computational expense, noise sensitivity and scale dependency, poor edge detection within medium-contrast images, large amount of training data required for the employment of neural networks and providing rapid automatic edge detection.

The AEDS is implemented to rapidly detect various military targets in low to medium contrast images. The camouflage targets comprise a military aircraft (JET), an armored tank (TANK), a military off-road vehicle (JEEP), a rocket launcher (SCUD) and a navy boat (BOAT). All five objects have had their images obtained in three different possible situations.

#### II. Scale Space Analysis

There are two phases of implementing the AEDS. The first (the Preparation Phase) uses a fast format of the Laplacian of the Gaussian (FLoG) edge detection operator [1][2], as shown below in (1). The FLoG operator is convoluted with a number of images that represent the training set of images for the neural network, at seven scales in scale space. The standard deviation  $(\sigma)$  of the Gaussian function in the FLoG operator is variable and it dictates the amount of smoothing to be imposed on the image prior to edge detection [3]. The high computations involved in multiscale processing, can be marginally reduced if a suitable scale is found, and then used [4][5]. A criteria for selecting the 'ideal edge detection at one ideal scale ( $\sigma_{Ideal}$ ) is set up, based on the convolution results using 3-dimensional objects [6]. The results of this phase represent the training data for the neural network arbitration in the second phase.

$$\nabla^2 G(x, y) = h(x)g(y) + g(x)h(y) \tag{1}$$

whereby

$$h(\xi) = \sqrt{A} \left( 1 - \frac{\xi^2}{\sigma^2} \right) e^{-\frac{\xi^2}{2\sigma^2}}$$

$$g(\xi) = \sqrt{A}e^{-\frac{\xi^2}{2\sigma^2}}$$

### III. Neural Network Arbitration

The second phase (the Training Phase) in the implementation of the AEDS is training a neural network to recognise  $\sigma_{Ideal}$  for an input image. This is based on the hypothesis that  $\sigma_{Ideal}$  is a function of noise [7], as in (2).

$$\sigma \sim \frac{1}{N}$$
 (2)

where,  $\sigma$  is the ideal scale ( $\sigma_{Ideal}$ ) and N is the

amount of noise present within the image. The trend of this non-linear relationship is what the neural network will be trained to recognise. The basis of the methodology is that the alteration in the amount of noise present within the image causes a change in the choice of the ideal scale  $\sigma_{ldeal}$  and thus the ideal edge detection of the image [8]. The presentation of various images and their corresponding ideal scales  $\sigma_{ldeal}$  will teach the neural network this relationship that is impossible to solve using conventional techniques. Having learnt successfully, the neural network will be capable of selecting only one ideal scale at which scale space edge detection can be carried out.

#### IV. The Training Data

Various three dimensional objects have been chosen and they represent potential real-life military camouflage targets. Their two-dimensional projections have been captured and used for the implementation of the neural system (AEDS).

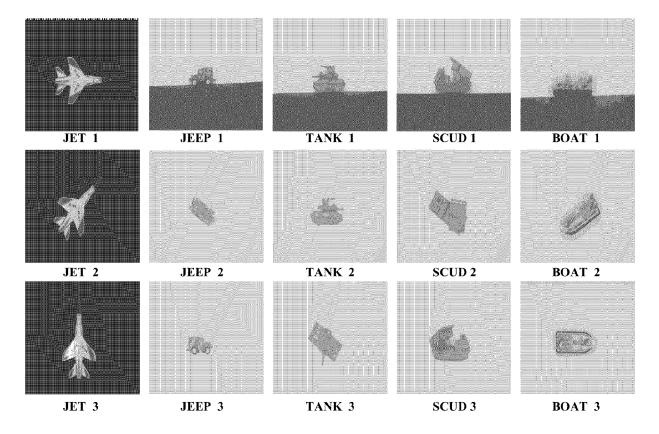


Figure 1. Images of military targets

The various objects comprise a military aircraft (JET), an armoured tank (TANK), a military off-road vehicle (JEEP), a rocket launcher (SCUD) and a navy boat (BOAT). All five objects have had their images obtained in three different possible situations, thus resulting in fifteen images available for the implementation of the automatic target detection system. Figure 1 shows the various original military target images.

#### A. The Preparation Phase

The first phase of the AEDS is implementing scale space analysis. Military images will be analysed using scale space, thus providing the ideal detection, represented through the ideal scales,  $\sigma_{Ideal}$ , for the various military targets.

The evolution of the military objects' edges in scale space can exhibit very many scales for certain images, and the scale space events that occur could lead to the disappearance of the object. This depends mainly on the background and how well camouflaged the target is. Figures 2 and 3 show two examples of the series of scale space events that occur on two of the targets. These are JET 2 and TANK 2 respectively.

The results of applying the first phase of the AEDS, that is the scale space analysis, have led to identifying the ideal scales at which the edge detection operator the Fast Laplacian of the Gaussian (FLoG) is to be applied. All the necessary data for the implementation of the second phase of the automatic edge detection scheme, which is the neural network recognition of the ideal scale ( $\sigma_{\text{Ideal}}$ ),

have been prepared. Table 1 describes the fifteen military images together with their ideal scales  $(\sigma_{\text{Ideal}})$ .

### B. The Training Phase

The second phase of the AEDS is implementing neural network arbitration. This phase involves training a neural network to recognise and select the ideal scale ( $\sigma$ ) for the edge detection for any military image. The neural network will be trained to relate the noise and the intensity within the images to their ideal scales,  $\sigma_{Ideal}$ .

There are seven different scales used in our edge detection. These seven scales are sufficient to demonstrate the occurrence of scale space events on all the objects' edges available for the system implementation.

For the training purpose, ten out of the fifteen available images are used for training the neural network and for recalling. These ten images comprise the first two of each military object. That is the images with suffixes '1' and '2'. The remaining five images with suffixes '3' are used for testing the generalisation properties of the neural network to recognise the ideal scale for the military targets. For example; JET 1 and JET 2 are used for training, whereas JET 3 is used for generalising.

The multilayer perceptron neural network, which has been developed for the AEDS, is based on the back propagation learning algorithm, with the total number of three layers, comprising, input layer, hidden layer and output layer. The Acquisition of

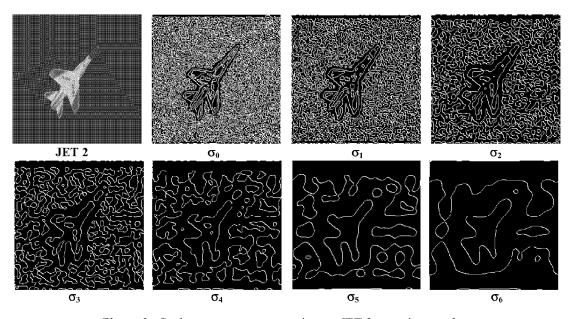


Figure 2. Scale space events occurring on JET 2 at various scales.

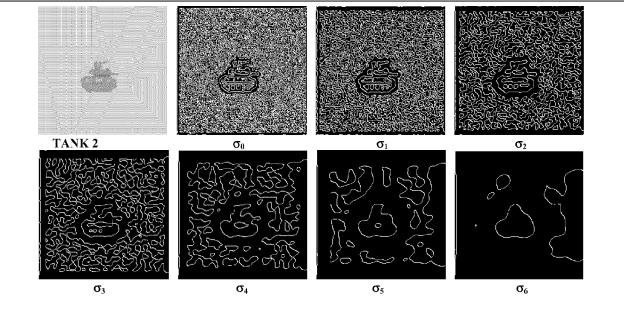


Figure 3. Scale space events occurring on TANK 2 at various scales.

on III 1	T 1 1	1			4.1	*1*4	•
Table I	Ideal	detection	ecales	tor	the	military	images
Table 1.	rucai	detection	scarcs	101	uic	11111111411 9	mnagos

JET 1	$\sigma_5$	JEEP 1	$\sigma_3$	TANK 1	$\sigma_2$	SCUD 1	$\sigma_3$	BOAT 1	$\sigma_3$
JET 2	$\sigma_5$	JEEP 2	$\sigma_1$	TANK 2	$\sigma_3$	SCUD 2	$\sigma_3$	BOAT 2	$\sigma_3$
JET 3	$\sigma_5$	JEEP 3	$\sigma_1$	TANK 3	$\sigma_3$	SCUD 3	$\sigma_3$	BOAT 3	$\sigma_3$

Table 2. Final neural network parameters for military targets.

Hidden	Learning	Momentum	Initial Weights	Error	Iterations	Training	Run Time
Nodes	Rate	Rate		Level		Time	
(H)	(η)	(α)	(W)	(8)	(I)	(Tt)	(Rt)
70	0.004	0.20	[-0.3 - +0.3]	0.0074	3000	4 hrs	0.63 s

Table 3. AEDS total running time at the various scales.

Ideal Scale ( $\sigma_{Ideal}$ )	$\sigma_0$	$\sigma_1$	$\sigma_2$	$\sigma_3$	$\sigma_4$	$\sigma_5$	$\sigma_6$
Scale Recognition Time (seconds)	0.63	0.63	0.63	0.63	0.63	0.63	0.63
Edge Detection Time (seconds)	1	2.66	6.03	12.91	26.29	53.92	107.58
Total Time (seconds)	1.63	3.29	6.66	13.54	26.92	54.55	108.21

the training data and presenting it to the neural network is very important, and care should be taken when selecting the training data. Manipulating the large amount of data available, when dealing with images, can be very computationally expensive and hence can take a long time. However, the use of a Sun-Sparc 10 running the UNIX operating system, together with C-language source code, provided a quick and powerful tool to optimise training time.

Thus, complying with the objectives of the neural system.

#### C. Results

The neural network converged and learnt in 4 hours, whereas the running time for the generalised neural network was 0.63 seconds. Table 2 lists the final parameters of the successfully trained neural network. In order to keep the learning time down, a

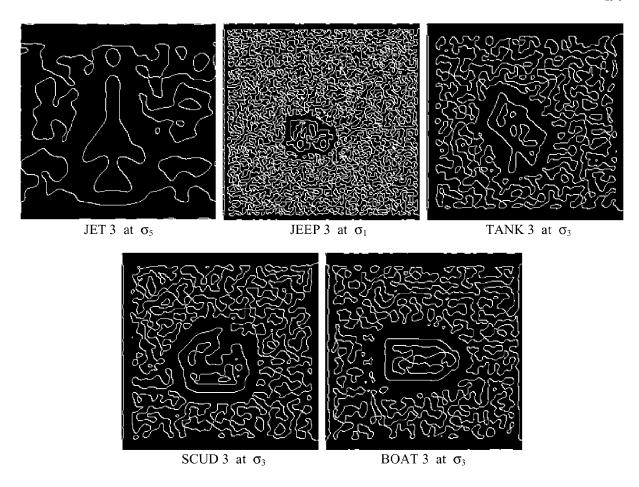


Figure 4. AEDS recognition of targets at their ideally-selected scales

minimum error of 0.0074 was regarded as adequate, as good recall and generalisation were obtained for the network. Table 3 shows the total running time for the AEDS at the various scales upon presenting an image to the system.

The robustness, flexibility and speed of the AEDS has been demonstrated through this application. The recalling of the ten training images was 100% successful, where all training images were allocated their correct ideal scales. The generalisation of the neural network, has also earned a similar success rate of 100%. The neural network recognised the correct ideal scales for the remaining 5 images, which it had not been trained on before.

The generalisation images, JET 3, JEEP 3, TANK 3, SCUD 3 and BOAT 3 can be seen in Figure 1. The ideal detection for the five targets as recognised by the neural system can be seen in Figure 4.

#### V. Conclusions and Further Work

The automatic edge detection scheme AEDS has been successfully applied to the recognition of camouflaged military targets. various implementation speed of 0.63 seconds is obtained when the neural network is used to generalise, as part of the complete automatic edge detection scheme. The total edge detection time including the automatic scale recognition time is in the range of (1.63 - 108.21) seconds; depending on the automatically selected ideal scale for edge detection. The necessary image data and information about enemy military targets can be, recurrently, used to train the AEDS in order to keep up-to-date information regarding any upgrades within the enemy military arsenal.

All the objectives which are outlined in the introduction section have been met, where:

- A remarkable scale recognition time of 0.63 seconds was achieved.
- High computational costs were reduced through using a fast edge detection operator that operates at one scale, rather than on a multiscale basis for an entire image.
- The AEDS is adaptable to the presence of noise and the variety of scale within the images. In fact, the novel technique utilises noise and scale information in order to produce an 'ideal' edge detection, thus making the AEDS ideal for implementation in other fields.

Further work can be carried out into implementing the AEDS in the rapid recognition of friendly military vehicles in action. This is necessary to avoid targeting own military arsenal, which could arise due to human misjudgment in real time.

#### VI. References

- [1] J.S. Chen, A. Huertas and G. Medioni, "Fast Convolution with Laplacian-of-Gaussian Masks", *IEEE Pat. Analys. and Mach. Intell.*, Vol. 9, pp. 584-590, 1987.
- [2] Marr and E.C. Hildreth, "Theory of Edge Detection", *Royal Soc. London*, pp. 187-217, 1980.
- [3] G.E. Sotak and K.L. Boyer, "The Laplacian-of-Gaussian Kernel: A Formal Analysis and Design Procedure for Fast, Accurate Convolution and Full-Frame Output", *Comp. Vision, Graphics and Image Processing*, Vol. 48, pp. 147-189, 1989.
- [4] T. Lindeberg, "Detecting Salient Blob-Like Image Stuctures and Their Scales with a Scale-Space Primal Sketch: A Method for Focus-of-Attention", *Int. J. Computer Vision*, Vol. 11, pp. 283-318, 1993.
- [5] T. Lindeberg, "Edge Detection and Ridge Detection within Automatic Scale Selection", *IEEE Conf. Computer Vision and Pattern Recognition*, pp. 465-470, 1996.
- [6] A. Khashman and K.M. Curtis "Scale Space Analysis Applied to 3-Dimensional Object Recognition", *E-LETTER on Digital Signal Processing*, Georgia Institute of Technology, Atlanta, USA, Issue No. 24, June 1995.

- [7] A. Khashman and K.M. Curtis, "A Novel Image Recognition Technique For 3-Dimensional Objects", *IEEE Int. Conf. (DSP'97)*, Santorini, Greece, 1997.
- [8] A. Khashman, "AEDS: An Edge Detection Scheme Using Scale Space Analysis And Neural Network Arbitration", *Ph.D. Thesis, The University of Nottingham*, UK, 1997.
- [9] A. Khashman, "Automatic Edge Detection of DNA Bands in Autoradiograph Images", Proceedings of the IEEE International Symposium on Industrial Electronics (ISIE'99), Bled, Slovenia, July 1999.